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International Journal of Innovation in Engineering

MICHAEL DAVID <mikeforheaven@futminna.edu.ng>

the reviews comments

1 message

ahmed.suleiman@federalpolyilaro.edu.ng <ahmed.suleiman@federalpolyilaro.edu.ng> 31 May 2025 at 21:51
Reply-To: "ahmed.suleiman@federalpolyilaro.edu.ng" <ahmed.suleiman@federalpolyilaro.edu.ng>
To: Associate Professor <mikeforheaven@futminna.edu.ng>

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Research Paper

Proposed Architecture and Mathematical Model to Enhance Interference Management in 5G-Enabled M2M Networks

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ABSTRACT

The growing number of connected devices has led to a significant shift in cellular standards, particularly with the Long-Term Evolution (LTE) framework. The fifth-generation (5G) standard supports several innovative mobile technologies, including Machine-to-Machine (M2M) communication and Device-to-Device (D2D) communication, enabling a vast network of interconnected intelligent devices. In Nigeria's power system, the deployment of M2M devices within the smart grid has introduced new challenges in resource allocation and interference management. The interference caused by reduced inter-cell distances and the seamless integration of heterogeneous devices into the 5G cellular network leads to a decline in Quality of Service (QoS) and overall network performance. In this paper, we propose an interference-aware architecture for Machine-to-Machine (M2M) communication within a smart grid. This architecture aims to mitigate the interference caused by the localization of M2M devices on the grid. Additionally, we will mathematically model the proposed interference mitigation scheme as a multi-objective particle swarm optimization problem, taking into account the complexity of the fitness function and the trade-offs between different particles. As a result of this approach, the interference generated by M2M devices will decrease significantly. Consequently, we expect to achieve a balance between the optimal separation distance of M2M devices and improved network performance.

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1. Introduction

The rapid growth of data-based services across networks has sparked a proportional surge in the use of cellular data transmission. A projected hundreds of billions of devices are expected to connect through the Internet of Things (IoT) to undertake different functions (Ghahremani-Nahr et al., 2022) (Garrido-hidalgo et al., 2023). The densified and varied communication network creates intense radio resource requirements that exceed scarce frequency spectrum capabilities, leading to various difficulties. Smart networked communication environments linking people and things together with applications and transport systems will ensure fast data transfer of large quantities through next-generation communication technology (Llerena & Gondim, 2020) (Bayanati, 2023b) (Uver, 2023). The foundational structure of communication networks will depend on cellular technology because it serves as the essential component to activate Internet of Things (IoT) devices and Machine-to-Machine (M2M) devices, as well as Device-to-Device (D2D) communication (Schianchi, 2023) (Bayanati, 2023a) (Ghahremani-Nahr et al., 2022). The key features of fifth-generation (5G) technology include standard infrastructure availability, easy installation and maintenance, massive machine-type connectivity, and enhanced speed.

The fundamental features that define 5G wireless systems separate them from other mobile broadcasting technologies, including Long-Term Evolution (LTE) networks and the Third Generation Partnership Project (3GPP). The current technological improvements fail to provide complete solutions for seamless services because of the increasing 5G user demands for mobile data (Agiwal et al., 2021). Through M2M communication, devices can connect to the network independently from multiple access points, eliminating the need for human involvement. Area reuse factor optimization and geographic proximity of neighbouring devices strengthen the efficiency of communication through this technology (Aliahmadi et al., 2022).

Two or more devices exchange data through M2M communication to connect all elements of the Internet of Things (IoT), which consists of multiple M2M connections spread across varied application domains. 5G cellular systems will deliver essential benefits that will enhance M2M communication deployments. The communication spectrum of M2M systems encompasses two principal categories: massive M2M (mM2M) and ultra-reliable M2M (uM2M). M2M technology allows wireless connection of multiple low-power, low-complexity devices, which include smart agriculture systems, wearable sensors, surveillance systems, smart grids, smart meters, health monitoring devices, industrial automation machinery, and intelligent transit terminals (Prathiba et al., 2024). The main goal of uM2M is to establish dependable wireless networks that fulfil strict demands concerning uptime and maintenance, and response times (Wu et al., 2020). The small data transactions in M2M setups make LTE and LTE-A technologies less suitable for these purposes. The primary purpose of these technologies was to serve wideband applications (Ahmed et al., 2023).

Smart grids achieve better resilience through M2M communication technology because they cut down the number of power outages triggered by grid failures that affect both distribution and transmission networks. Modern electrical power networks can be considered a contemporary framework because they automatically control the flow of energy between producers and end-users, transitioning traditional power delivery infrastructure into a cyber-physical platform. The system enables bidirectional communication, connecting generation sources with consumers. Intelligent energy management combined with efficient monitoring systems allows the successful management of energy transfers between RE sources and SG infrastructure while supplying power to the network. By implementing this method, the focus is placed on making energy efficiency irreversible (Amine et al., 2021). Multiple important goals comprise the optimization functions of smart grids despite M2M devices linking through spatial and temporal conditions. System optimization initiatives focus on maintaining stability and reducing costs in power generation to make the grid more resilient. Abdulsalam et al. (2023) explain that the additional optimization targets of smart grids aim to minimize pollution output, examine grid contingency data, and decrease distribution losses while enhancing voltage quality (Abdulsalam et al., 2023). The implementation of smart grid infrastructure depends on proper communication network designs for essential components, including smart meters, circuit breakers, transformers, feeders, substations, grid stations, and control centres (Raza et al., 2019). The network of SG devices utilizes M2M technology for monitoring traditional challenges, including scheduling, demand-side management, demand response, unit commitment, network grid configuration, contingency planning, distributed generation allocation, and transmission and generation expansion.

The combination of cellular components with smart grids allows new smart features to develop, including decentralized power generation and two-way energy trading and request coordination, and energy redistribution systems (Abrahamsen et al., 2021) (Hu et al., 2020). The smart grid achieves reliable energy automation services through its feature of two-way communication and electric flow capabilities (Khalid, 2024) (Majeed Butt et al., 2021). The investigation in this study focuses on a scheme that addresses the interference aspects of the proposed 750-kV Nigerian Power Grid. The Nigerian national power transmission network operates as the current electricity distribution system throughout the country. The power grid works with a radial setup while utilizing 4,889.2 km transmission lines and owning 49 operational buses, and delivering power generation capability of 6,000 MW (Abdulsalam et al., 2023).

Many technological challenges arise when managing interference caused by the growing number of M2M devices linked to various devices and the decreasing cell distances in cellular networks. Interference management becomes more complex because these factors create difficulties in distributing M2M communication resources. The reduction of channel capacity affects primary user communication quality as one of its main consequences (Song et al., 2020). The 5G network contains two primary types of interference systems: co-channel interference (CCI) and adjacent channel interference (ACI). Network architecture faces multiple challenges due to the system's densification and the presence of heterogeneous devices, as well as extremely close 5G cell configurations, which enable simultaneous information exchange among multiple devices. The resulting interference creates problems that reduce the standard of communications. Systems experience co-channel interference whenever they operate on identical frequency resources, and cross-channel interference occurs when cellular spectrum resources are reused with different frequency resources. Interference between similar transceivers occurs when they operate near each other within the communication range.

Key Contribution of this paper

The key contributions of this work are outlined as follows:

i. This research proposes the design and development of an interference-aware architecture along with an interference mitigation scheme specifically for 5G networks, with applications to the Nigerian Power Grid network.
ii. A mathematical model for the interference mitigation scheme is developed, framed as a Multi-Objective Particle Swarm Optimization (MOPSO) problem that includes distance, power, and bandwidth as the multi-objective parameters.

The structure of this paper is organized as follows: Section II discusses related works that underpin the fundamental concepts of interference. Section III introduces the proposed interference-aware architecture and the MOPSO scheme for interference mitigation. Section IV examines the expected results, and finally, Section V provides the conclusion.

2. Related works

Various methods have been adopted in literary discussions about interference management within Machine-to-Machine (M2M) communications under 5G network conditions. A combination of radio resource allocation and power control techniques and spectrum allocation strategies functions to resolve interferences in communication systems. AlSheyab et al. (2020) conduct research into how Network Flying Platforms affect interference in ultra-dense tiny cells. The authors present NP-hard issues and suboptimal solutions in their work while introducing a bipartite machine and a local search-based algorithm to minimize interference. The main drawback of their research emerges from not evaluating interference between different communication layers. The simulation ran successfully to minimize interference, as indicated by the results (AlSheyab et al., 2020). Cheng et al. (2021) present HAPPIER as a learning-based system for interference management within unmanned aerial vehicle-mounted tiny cells. Autonomous Small Cells (ASCs) transmission power is managed by this system while it addresses co-channel interference. Hybrid affinity propagation clustering is combined with reinforcement learning to enhance both learning rate and transmission power efficiency within the system. The gearbox power adjustment technique enables the system to reach 93% of maximum throughput when compared to exhaustive search. Cross-interference issues related to M2M communication served as the core subject of their research, yet their study excluded analysis of co-channel and mutual interference from its interference theory (Cheng et al., 2021).

Dubey et al. (2020) developed an effective plan to minimize network interference, which enhances system throughput for machine-to-machine (M2M) cellular devices. The system implements three components, including cell subdivision-based resource distribution and channel allocation strategy with reliable particle swarm optimization for power allocation in mid-cells. Simulation findings indicate that throughput improvement occurs due to better interference reduction; however, network throughput drops sharply when the M2M pair distances reach this critical threshold. The study scope only consists of examining co-channel and cross-channel interference, but does not evaluate mutual interference (Dubey et al., 2020). The eNodeB transmission power reduction leads to a detrimental effect on the signal-to-interference plus-noise ratio (SINR), according to Kumar et al. (2021). The research demonstrates improved SINR as throughputs increase, and when outages happen, but the investigation excludes analysis of neighbouring cell interference (Kumar et al., 2021).

Barman and Ajay (2020) established a collaboration framework that manages resource distribution combined with mode selection and interference cancellation operations for public safety and ubiquitous networks based on the licensed cellular band M2M communication system. The researchers applied orthogonal precoding alongside power control mechanisms to develop improved modes and reduce interference between adjacent cells that operate from the same spectrum band. The proposed orthogonal precoding method outperformed conventional precoding techniques in regions with high interference, as indicated by simulation results. The research analysis did not include an examination of interference between M2M networks that share the same tier or mutual interference between devices (Barman & Roy, 2020). A data rate optimization method under transmit power and SINR constraints involves the joint application of power control with interference-limited areas (PC-ILA) according to (Liu et al., 2020). The method achieved superior performance compared to past systems for total data rate calculations across high-load conditions, which simultaneously boosted coverage probability and improved mode selection operations in strong SINR regions.

The Enhanced Active Power Control (EAPC) technique emerged as a solution to interference problems, according to the research by (Dawar et al., 2021). While considering only cross-tier interference, the simulation outcomes show that this approach delivers the maximum throughput along with minimal power usage compared to other tested techniques. The Soft Frequency Reuse method proposed by Osama et al. (2021) utilizes ICR-based On/Off switching to minimize power usage, while also eliminating interference. The system achieves its maximum expected data speed when the strategy selects the most appropriate device center radius area. Power usage reached its minimum point when eNodeBs were deactivated while keeping Machine-to-Machine (M2M) devices operational, according to simulated results. The examination emphasized co-tier interference as its only analysis subject (Osama et al., 2021).

Wang et al., (2021) provided a solution which combines limitations in spectral resources with power management optimization strategies for Machine-Type Devices (MTDs). The algorithm drives spectrum resource allocation towards MTDs that cause more interference by using a reduced greedy version of channel allocation known as Iterative Channel Allocation and Power Control. When tested through Monte Carlo simulations, the proposed algorithm matched the optimal minimum Signal-to-Interference-plus-Noise Ratio (SINR) in 99.5% of cases. The SINR performance exhibits minor fluctuations as the SNR increases, due to diminishing MTD distances while the number of MTDs simultaneously increases (Wang et al., 2021). Moreover, Das and Hossain (2020) developed a location-aware power control method for M2M cellular networks by implementing a water-filling algorithm and optimizing the Lagrange decomposition scheme. Through this approach, the system achieves better interference control, operational spectrum, and energy efficiency. The proposed method addresses multiple restrictions that involve User Equipments (UEs), transmission power, mode selection thresholds, M2M data rates, and cellular network interactions with M2M components. The main drawback of this approach was determining the optimal M2M pair distances to achieve peak data rates (Das & Hossain, 2020). The study investigated by Hassan and Fernando (2019) recommended a location-based strategy to reduce base station (BS) network cross-tier and co-tier interference. This method analyzes received SINR values in conjunction with user mobility and traffic flow behavior within the network, as well as system-wide load conditions. A joint solution of location-based algorithms and user-shared load data enabled them to minimize both cross-base station interference patterns and co-interference conditions. The proposed method causes load imbalances because it ignores multiple network aspects when assigning Max-SINR user associations. The approach did not consider the effects of M2M device interferences, nor the interactions of M2M-eNode systems, nor the interferences between M2M devices (Hassan & Fernando, 2019). A study conducted by Pourkabirian et al. (2021) presented a game theory strategy for achieving power optimization within 5G femtocell networks. The approach used iterative learning to set user transmission power levels, solving them with QoS requirements and interference limitations in mind. The simulation yielded positive outcomes, improving system throughput, QoS, and reducing interference levels (Pourkabirian et al., 2021). The summary of the related works is depicted in Table 1 below.

Table 1: Summary of related work

S/No.	References	Problem formulation	Optimisation Technique	Drawback
1	(AlSheyab et al., 2020)	Integer Linear Programming	Bipartite matching and local search-based algorithms	Cross-tier interference was not considered
2	(Cheng et al., 2021)	Non-convex optimisation problem	Hybrid Affinity Propagation Clustering and Reinforcement learning power control mechanism (HAPPIER)	Co-tier and mutual interferences were not considered
3	(Dubey et al., 2020)	Mixed-Integer Non-Linear Programming (MINLP) problems	Single objective PSO	Mutual interference was not considered. The distance and channel allocation were not considered within the scope of the study.
4	(Kumar et al., 2021)	Non-convex optimisation problem	Successive-Interference-Cancellation technique	Cross-tier interference was not considered
5	(Barman & Roy, 2020)	Mixed-Integer Non-Linear Programming (MINLP)	orthogonal precoding technique and a power control	Co-tier and mutual interference were not considered

6	(Liu et al., 2020)	Mixed-Integer Non-Linear Programming (MINLP)	Power Control with Interference Limited Area (PC-ILA) technique	Cross-tier and mutual interference were not considered.
7	(Wang et al., 2021)	Combination of Mixed integer and binary integer programming problem.	iterative channel allocation and power control algorithm (ICAPCA) and greedy channel allocation algorithm (GCAA)	Cross and co-tier interference were not considered.
8	(Das & Hossain, 2020)	A dual optimisation problem was formulated	A water filling algorithm and Lagrange decomposition scheme-based power optimization	Co-tier and mutual interference are not considered in the study
9	(Hassan & Fernando, 2019)	Non-Linear Optimization	a location-based interference mitigation algorithm that	Mutual interference was not considered

Current interference mitigation strategies fail to meet comprehensive standards according to the different techniques observed by numerous researchers. The research fails to examine all three types of interferences, which include cross-tier interference, co-tier interference, and mutual interference, according to the study design. The present research has been justified by an identified gap in existing knowledge.

3. System Model and Problem Formulation

The research focuses on a scheme for the integrated 750-kV Nigerian Power Grid that serves as the backbone supply system for Nigerian electricity distribution across the country. Transmission lines spanning 4,889.2 km service 49 operational substations while supplying electricity to customers through 6,000 MW of available power generated by 19 facilities that have hydroelectric and gas-powered capabilities (Abdulkareem et al., 2021). Figure 1 shows Machine-Type Devices (MTDs) that are integrated throughout the power grid network, including smart meters, circuit breakers, transformers, feeders, substations, control centres, and grid stations (Raza et al., 2019). The deployment of eNodeBs occurs randomly across cellular cells to enable uninterrupted data exchange between Cellular User Equipments (CUEs) and Machine-Type Devices (MTDs). Figure 1 shows that MTD density alongside short inter-cell distances produces interference problems that hurt the main users referred to as CUEs.

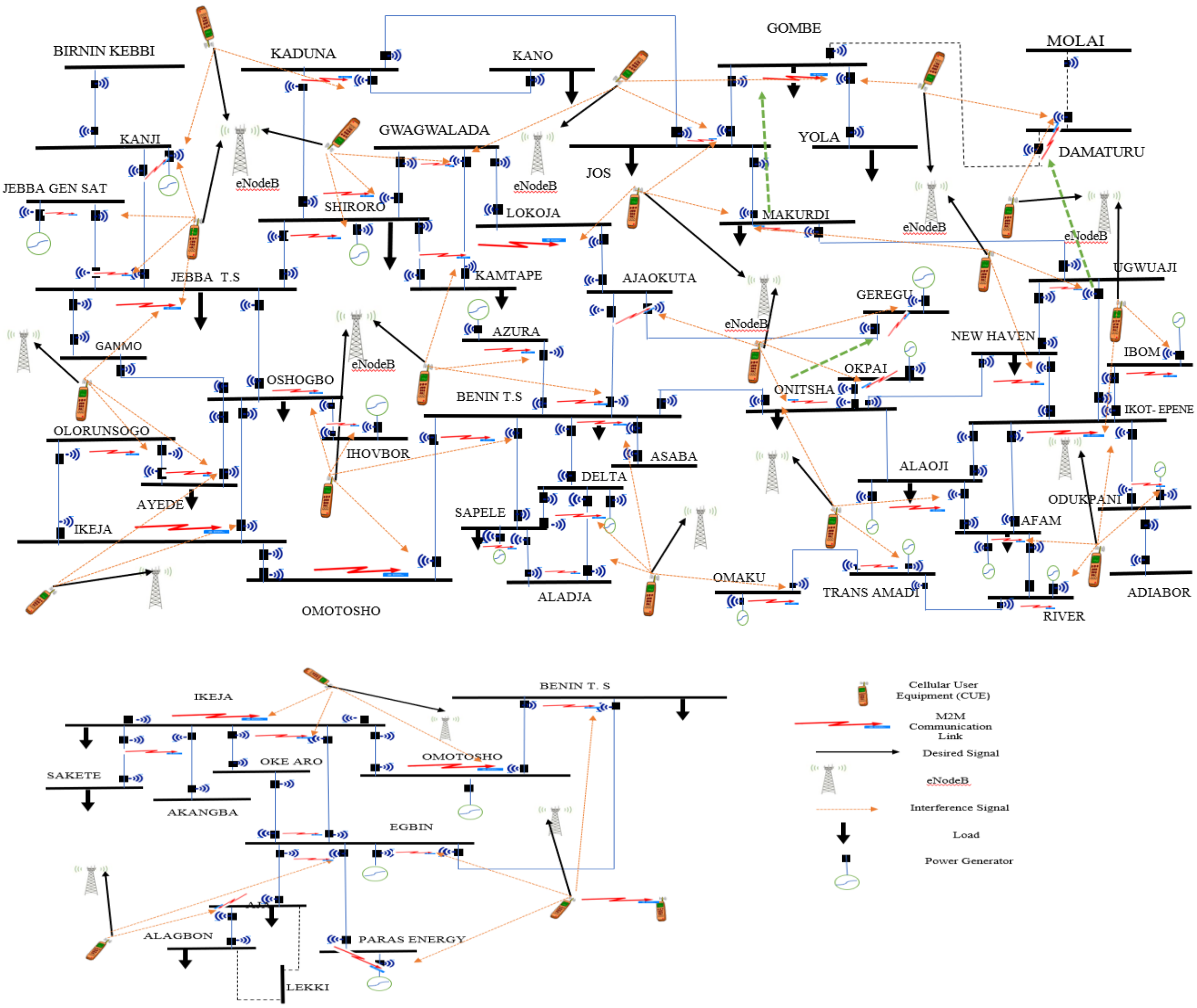

Figure 1: Smart Integrated 750-kV Nigerian Power Grid

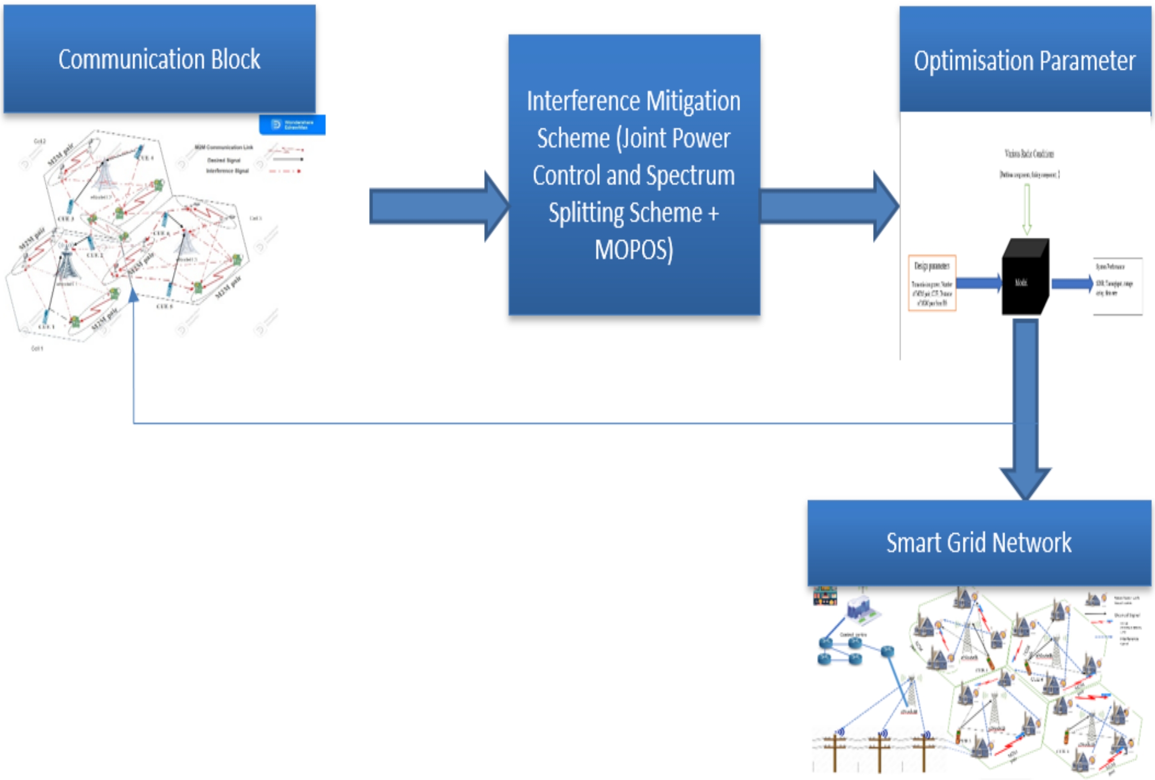

Figure 2: The block diagram of the proposed interference-aware scheme

3.1. System Model

To formulate the model, it is essential to define the problem. This involves minimizing interference and energy consumption in M2M (Machine-to-Machine) communication while maximizing throughput as the distance between machines varies. Additionally, the optimization problem is structured as a multi-objective function. For the practical application of this study, we consider a multi-cell system in which mobile terminals and neighbouring base stations communicate across a coverage area, specifically in relation to the Nigerian power grid. This assumes the placement of M2M devices that cover the power grid. The core concept of multi-cell M2M communications within the coverage of a smart power grid, underpinned by 5G cellular networks, is illustrated in Figure 1. In our system model, we focus on the distribution of resources for reusing cellular uplink radio resources. We adopt a centralized resource allocation architecture, where the eNodeB (evolved Node B) governs radio resource allocation. Figure 2 presents a diagrammatic representation of the overall model, showcasing the parameters, network constraints, and system performance metrics.

3.1.1. Communication Block:

The communication block comprises all the equipments that facilitate the connection between various devices in the 5G cellular network, namely:

i. **Base Station**: A cellular network's base station, commonly known as a cell site, typically consists of a tower and an equipment house. Each cell site is usually designed to accommodate multiple cell towers, with each tower serving a specific area within the surrounding region. The base station hardware that manages the radio interface with mobile devices is referred to as the "eNodeB." The eNodeB oversees not only the radio communication protocols with mobile devices but also manages the radio resources for the cell. Additionally, it handles functions such as handover, authentication, and mobility management. A high-speed backhaul link connects the eNodeB to the core network, which is typically managed by a network management system (Rao et al., 2022).

ii. **Cellular User Equipments (CUEs):** These are primarily handheld or mobile devices that act as the communication link between the user, the base station, and multiple other users located in various places (Alves et al., 2021). In addition to their essential role in communication, these devices also fulfill other needs, such as entertainment and work-related tasks, for users.

iii. **Machine-to-Machine (M2M)/Machine-Type-Devices (MTDs):** The goal of Machine-Type Communications (MTC) is to provide access services for various Machine-Type Devices (MTDs) without requiring human involvement. MTC is considered one of the three generic service categories of the 5G system. It plays a crucial role in numerous applications, including real-time monitoring, control, and industrial automation, which demand strict specifications for minimal latency (Luo et al., 2021). These devices are integrated into switches, relays, transformers, and cameras in both industrial and home environments.

3.1.2. Interference Mitigation Scheme:

The system model presented in section 3.1 will be optimized using a newly designed interference mitigation scheme. This scheme will include a joint power control technique and spectrum splitting, implemented through a Meta-heuristic Multi-objective Particle Swarm Optimization approach. This enhanced strategy will effectively reduce the interference caused by the integration of Multi-Technology Devices (MTDs) into the 5G cellular system, while also ensuring efficient resource allocation.

3.1.3. Optimisation Parameters:

The model outlined in section 3.1.1 was mathematically modelled using the simulation parameters. Additionally, the radio condition requirements are illustrated in Figure 3.3. The parameters used for the model simulation include the transmit power for both the CUEs and MTDs, the spectrum bandwidth, and the separation distances between M2M pairs.

i. **Transmit Power:** The transmit power for the CUEs in the model was simulated at 100mW. The MTDs have a transmit power of 17.23dBm, and the eNodeB has a transmit power of 2W.

ii. **Spectrum Bandwidth:** The spectrum sub-channel bandwidth was simulated using a bandwidth of 0.3215MHz for the MTDs.

iii. **Separation Distance:** Within the cells, the CUEs are uniformly distributed, whereas the MTD pairs were simulated with a separation distance of 20 m between each pair.

3.2. Problem Formulation

In this network utilizing Orthogonal Frequency Division Multiple Access (OFDMA), there are Z sub-channels available, with K Machine-Type Devices (MTDs) coexisting alongside L Cellular User Equipment (CUEs) within each serving eNodeB. We assume that all eNodeBs in the network are identical, have the same bandwidth, and are divided into several channels of similar bandwidth sizes. Furthermore, we operate under the assumption that the cellular network is functioning at maximum capacity, with the number of available channels for uplink transmission being equal to the number of CUEs in each eNodeB. Furthermore, it is also assumed that M2M links share $z-th$ uplink channel (UL) $Z_C=\{1,2,3,.......Z\}$, which are used by the cellular user. Let the index sets of the cells, CUEs/channels, and MTDs be represented by $eN_s=\{1,2,3.........eN_{sm}\}$, $\mathrm{P}=\{1,\ 2,3,...,\ \mathrm{Z}\}$ and $\mathrm{Q}=\{1,\ 2,3,..,\ \mathrm{K}\}$ respectively. It is equally assumed that $\kappa=[1,2......K]$ is a set of Resource Blocks, and we assume that each M2M pair uses one RB and that each RB can be shared by one M2M pair. We consider a fully loaded network where M2M pairs can only connect by sharing RBs with CUEs. An MTD (Machine-Type Device) pair consists of a receiver (M2M-Rx) and a transmitter (M2M-Tx) that do not need to be located within the same cell when communicating directly with the serving eNodeB. As illustrated in Figure 1, an M2M device (M2M-Tx) can communicate directly with another M2M device (M2M-Rx) if the M2M-Rx is within the transmission range of the M2M-Tx. It is assumed that frequency reuse in the network is equal to one, meaning that CUEs (Cellular User Equipment) in nearby eNodeBs can interfere with MTDs in the serving eNodeB. While the eNodeB can calculate the Channel State Information (CSI) for cellular uplinks from CUEs, the CSI for M2M communication links must be estimated directly by the MTDs. This estimated CSI is then sent back to the eNodeB, which reports it using the uplink idle band. Peer device discovery and session setup are assumed to occur before resource allocation is initiated. The eNodeB is considered to have perfect CSI for all links, and both CUEs and M2M pairs must meet their minimum Quality of Service (QoS) requirements in terms of Signal-to-Interference-plus-Noise Ratio (SINR) on the $z-th$ channel. To facilitate communication, M2M devices establish routes among themselves. With this practical framework in place, MTDs can be allocated resource blocks (RBs) alongside a power control scheme for effective communication.

In this section, we will examine the outage probability associated with a pair of Machine-Type Devices (MTDs) randomly positioned within a cell. We employ a geometric approach to derive the outage probability between the MTDs and the Cellular User Equipment (CUE), taking into account their random distances and the probability distribution of their fading channels. Furthermore, Figure 1 illustrates the implementation of Machine-to-Machine (M2M) communication within a smart power grid under a 5G cellular network. The integration of MTDs into the power grid improves data throughput, reduces transmission delays and network downtime, and minimizes power loss across the grid.

Our objective is to determine an efficient joint channel allocation and power control approach for every M2M transmitter in the multi-cellular scenario, considering various QoS requirements. We assume that M2M users have K service kinds, represented by $F_k \in \{F_1, F_2, F_3 \ldots\ldots F_K\}$ and that the channel transmission rates needed for each service vary. We assume that a M2M pair can meet the QoS requirements of the entire communication system with minimal power consumption by reusing multiple channel resources to assure packet transmission success. Furthermore, the CUE's signal to signal-to-interference-plus-noise-ratio (SINR) can be written as $\xi_j^{C_n}$. The SINR must be higher than ξ^* for transmission to be successful. Where ξ^* the threshold for different M2M devices placed with the power grid.

Therefore,

$$\xi_j^{C_n} > \xi^*, \; \forall j \in N \qquad (1)$$

For the nth M2M link on the j th channel, the SINR is expressed as:

$$\xi_j^{M_n} = \frac{P_j^{M_n} e_j^{M_n}}{P_j^{C_m} e_j^{C_m} + \sum_{h=1, h\neq n}^{N} P_j^{M_h} e_j^{M_h} + N_a + \sigma^2} \qquad (2)$$

Where $P_j^{M_n}$ is the transmit power on the M2M link on the j th channel and $e_j^{M_n}$ denotes the channel gain between the M2M-Tx and M2M-Rx, respectively. Moreso, $P_j^{C_m}$ on the j th channel represents the transmit power by the m th CUE and $P_j^{M_h}$ denotes the transmit power of the h th M2M link. The link gain of the m th CUE and h th M2M link on the j th channel are denoted by $e_j^{C_m}$ and $e_j^{M_h}$ respectively. The Additive

White Gaussian Noise (AWGN) power is given as σ^2, N_a represents the average interference (Noise) emanating from other surrounding neighbouring cells, which can be expressed as:

Similarly, the SINR of the m th CUE on the j th channel can be denoted as:

$$\xi_j^{C_n} = \frac{P_j^{C_m} e_j^{C_m}}{\sum_{i=1}^{K} \sum_{y=1,}^{N} P_i^{M_y} e_i^{M_y} + N_a + \sigma^2} \qquad (3)$$

Where the transmit power of the m th CUE and the transmit power of the y th M2M link that reuses the i th channel is given as $P_j^{C_m}$ and $P_i^{M_y}$ respectively, while the channel gain of the m th CUE and the channel gain of the y th M2M link reusing the i th channel is denoted as $e_j^{C_m}$ and $e_i^{M_y}$ respectively as shown in equation 3.

$$N = E \cdot \sum P_w \cdot S_w^{-\alpha} \qquad \forall w \in \{1,2,3,....W\} \qquad (4)$$

Where S is the sum of the Euclidean distance between two M2M pairs and the CUE, w represents the number of neighbouring cells, E is the link gain. However, the distance between the CUEs and the M2M pair can be expanded and represented relative to the coordinates of the various devices. Considering ($s_{i,b}$, $s_{j,b}$) and (s $s_{i_1,b}$, $s_{j_1,b}$) as the coordinates of the positions of the M2M pairs and a cellular user, then the distances are the Euclidean distance between two M2M pairs $s_{j,j}$ and the cellular $s_{i,j}$ is given as:

$$s_{j,j} \le \left(\frac{s_{i,j}^{\alpha} (\Omega - 1) s_{j,b}^{\alpha} e_{j,j} e_{i,b} \left(\overline{e_{j,b}} \right)^{-1}}{\xi_j^m e_{j,j} \left[\Omega \xi_i^{c,b} s_{i,b}^{\alpha} e_{i,j} + s_{i,j}^{\alpha} e_{i,b} \right]} \right)^{\frac{1}{\alpha}} \square\ s_{\max} \qquad (5)$$

Where $s_{\max}$ signifies the maximum transmission distance of the M2M source. This further defines the location of the destination where the M2M receiver must be localised in order to attain the required minimum SINR $\xi_{j,\min}^m$ of the M2M. The distances between the CUE and the M2M devices, the distance between the M2M-TX and the eNodeB, and the distance between the CUE and the eNodeB are represented as $s_{i,j}^{\alpha}$, $s_{j,b}^{\alpha}$, $s_{i,b}^{\alpha}$ respectively. Furthermore, $e_{j,j}$, $e_{i,b}$, $e_{i,j}$ $\overline{e_{j,b}}$, denotes the gain between, the M2M-Tx and M2M-RX, the CUEs and eNodeB, the CUEs and M2M devices, and the estimated gain between the M2M devices and eNodeB respectively. Where Ω represent the scaling factor. In order to satisfy the SINR constraint for an M2M link and avoid outage, the link probability is given as $\Pr\left[s_{\max} \ge s_{j,j} \right]$. The overall system capacity of a given cell is expressed as:

$$\max_{\omega_{i,j}, P^m{}_j} R_{overall} = \sum_{b \in N_s} \sum_{i \in P} \left[B(\log_2(1 + \xi_j^{C_n}) + \sum_{j \in Q} \omega_{i,j} \log_2(1 + \xi_j^{M_n})) \right] \qquad (6)$$

Where B represents the bandwidth.

3.3. Joint spectrum splitting and power control method with Multi-Objective Particles Swarm Optimisation (MOPSO) Technique

The popular population-based metaheuristic method known as particle swarm optimisation was motivated by the social behaviour of particles, such as the movement of fish or birds. The primary parameters in this algorithm are the position and velocity of each particle. Based on its own experiences and those of its neighbouring particles, each particle modifies its position inside the multidimensional search space. Local and global search techniques are combined in the PSO approach (Yuan et al., 2023). The particle's initial position is chosen at random to begin the PSO algorithm's initialisation, after which the objective function is used to determine the fitness value. In every iteration, every particle moves closer to the two optimal values, Pbest and Gbest. Gbest is the population's best answer, while Pbest is the best solution each particle has produced. In this paper, after interacting with the surroundings, the M2M transmitter learns an effective joint channel splitting and selection with a power control policy. Generally speaking, when more M2M users utilise the cellular channels, the transmission power of M2M users increases, and cellular users experience increased interference. Our methodology maximizes SINR and system ergodic capacity while satisfying service expectations by allowing each M2M pair to adaptively optimize and trade off multi-object particles (channel bandwidth, optimal M2M separation distance, and power control methods). Using Multi-objective Particle Swarm Optimisation (MOPSO) techniques can help tackle the aforementioned challenge, which is a complex multi-objective dilemma.

The swarm particles are initialised based on the criteria that each particle (X) is an optimisable parameter for multi-objective problems. The particle symbolises the potential solution for distance, channel bandwidth, and power transmission. However, the velocities and position of the particle are randomly initialised.

3.3.1. Particle Initialisation

$$X = [Power, Bandwidth, Distance] \qquad (7)$$

Each of the particles is expressed as a vector, and with several particles populations can be given as follows:

$$X_{i,j} = [P_{i,j}, B_{i,j} \ \ D_{i,j}] \qquad (8)$$

$$X_{i,j} = \begin{bmatrix} {P_{i,j}}^{n} \\ {B_{i,j}}^{n} \\ {D_{i,j}}^{n} \end{bmatrix} \qquad (9)$$

Where **P**$i,j(n)$ is the Power parameter P for the n-th sample at position (i,j), **B**$i,j(n)$ is the Bandwidth parameter B for the n-th sample at position (i,j), **D**$i,j(n)$ is the Distance parameter D for the n-th sample at position (i,j).

3.3.2. Fitness Evaluation:

The interference mitigation scheme is designed to optimise the crucial objective functions that significantly contribute to the influence of interference when underlay in a 5G network. Hence, the resultant interference from the integration of M2M devices with the primary users' CUEs, thereby achieving effective spectrum allocation within the optimal separation distance and optimal power allocation. The objective function utilised in this study can be expressed as:

i. Maximise the SINR to ensure the quality of communication is of high fidelity.
ii. Maximise system throughput for efficient information transmission.

Therefore, the maximisation of the sum of SINR and the overall system throughput can be expressed as:

$$maximize\ \left(F(X_{i,j})\right) = \ [SINR,\ Th_{overall}] \tag{10}$$

Subject to:

1. $P_{\min} \le P_i \le P_{\max}$
2. $B_{\min} \le B_i \ \le B_{\max}$
3. $D_{\min} \le D_{i,j} \ \le D_{\max}$

Where $P_{\min}$ and $P_{\max}$ represents the minimum and maximum transmission power limits, $B_{\min}$ and $B_{\max}$ denotes the minimum and maximum bandwidth limits, and $d_{\min}$ and $d_{\max}$ are the minimum and maximum distance limits.

3.3.3. Velocity and Position Update

For each particle (X), the velocity and position are regularly updated using the standard PSO equation. Each particle in the network updates its position and velocity based on its current position, personal best, and global best. The rule governing the velocity update is given by (11).

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (p_i^{(t)} - x_i^{(t)}) + c_2 r_2 (g^{(t)} - x_i^{(t)}) \tag{11}$$

Where $v_i^{(t)}$ is the velocity of the particle i at time t, w is the inertia weight (controls the exploration vs. exploitation trade-off), c_1 and c_2 are cognitive and social acceleration coefficients, respectively. It is via the modification of c_1 and c_2 that the MOPSO could attain the required trade-off between cognitive and social behavioural patterns, r_1 and r_2 are random numbers uniformly distributed between 0 and 1, $p_i^{(t)}$ is the personal best position of the particle i, and $g^{(t)}$ is the global best position that has been explored by all the particles across the swarm. The particle's position is updated as:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{12}$$

3.3.4. Non-Dominated Sorting and Pareto Front Update

After the particles have completed the process of updating their velocity and positions, the algorithm further evaluates the values of the objective function and updates the Pareto front. The non-dominated sorting technique is utilized for multi-objective optimization to identify solutions that no other solution dominates in both objectives (Pareto Optimal solutions). A solution x_i dominates another solution x_j based on the below-stated condition:

If and only if:

1. $SINR_i \ge SINR_j$ and $Throughput_i \ge Throughput_j$
2. At least one inequality is strict.

3.3.5. Archive Update

The archive stores several non-dominated solutions based on the Pareto optimality condition. The archive has been updated regularly when new best solutions are obtained.

3.3.6. Convergence Check

Convergence is attained based on the condition that the Pareto front is met or the predefined number of iterations is reached; otherwise, the algorithm returns to the velocity and position update. Once the algorithm has converged, it terminates, and the resultant solution produces a set of Pareto-optimal solutions, each of which signifies the trade-off between maximising the throughput and maximising the SINR. Hence, the final decision depends on the preferred network requirement. Figure 3 illustrates the flowchart of the proposed MOPSO scheme.

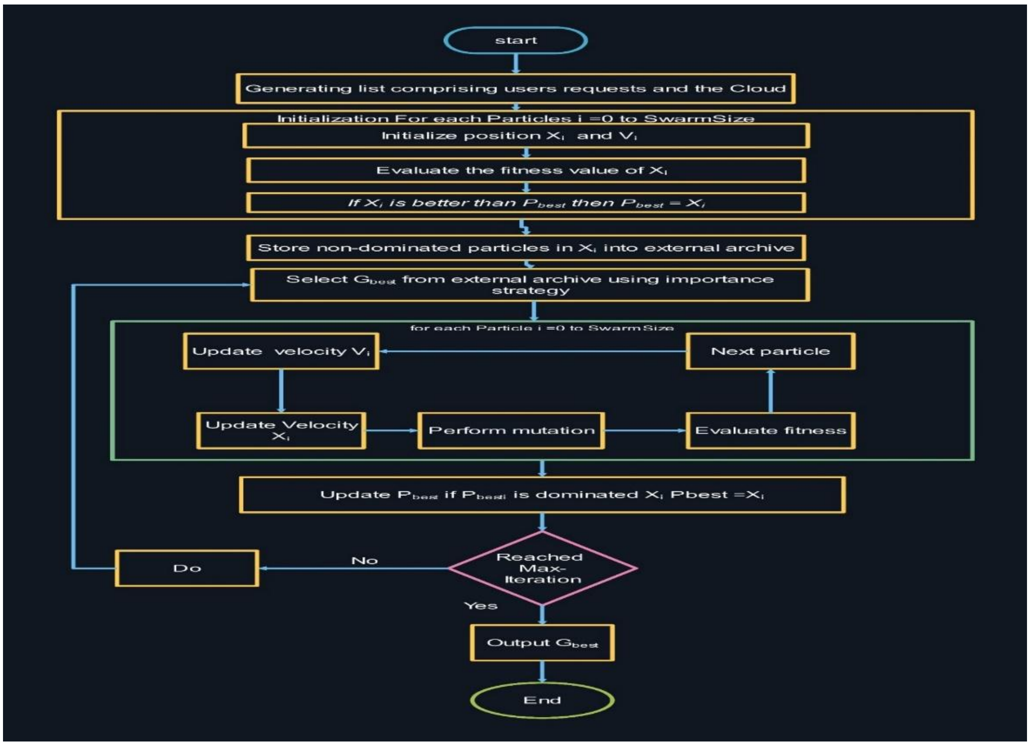

Figure 3: The flow chart of the Multi-Objective Particle Swarm Optimisation (MOPSO)

4. Expected Results

It is anticipated that by the end of the simulations, the proposed interference mitigation scheme will significantly reduce the interference caused by the deployment of Machine-Type Devices (MTDs) on the smart grid, particularly due to the decrease in inter-cell distance. However, the degradation of the channel caused by co-tier and cross-tier interference may increase. This increase will be mitigated through effective resource allocation utilizing the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which will ensure optimal channel assignment and power allocation for each particle in the swarm, including the Cellular User Equipments (CUEs). As a result, the distance parameter will contribute to the optimal placement of the Machine-to-Machine (M2M) devices on the smart grid, ultimately improving the latency of communication between M2M pairs. This enhancement will result in reduced downtime of the power grid and faster recovery times for M2M devices affected by network interference.

5. Limitations of the Study

MOPSO demonstrates high computational complexity during multiple-objective optimization procedures, where the simultaneous optimization of Signal to Interference plus Noise Ratio (SINR) and throughputs occurs. Real-time application presents execution hurdles, particularly among large-scale M2M networks that contain dense implementations of devices. MOPSO typically selects suboptimal solutions when solving problems with highly complex, non-convex, or multi-modal optimization landscapes. The success of MOPSO depends heavily on adjusting its parameters, such as inertia weight and cognitive and social coefficients, to prevent the generation of inadequate solutions. Increasing both the size of the network and the number of M2M devices introduces higher dimensions into the optimization process, and consequently slows down convergence. Swarm optimization of high-dimensional problems tends to either make particles stop moving or reduce the diversity of swarm members. MOPSO exhibits limited responsiveness when encountering rapid changes in interference levels, as well as shifting device locations within real dynamic 5G communication networks. The process of repeated optimisation requires additional computation time as well as longer response delays.

The optimisation procedure becomes more complicated when multiple objectives, including Signal-to-Interference-plus-Noise Ratio (SINR), throughput, and Quality of Service (QoS), are incorporated together, making the optimisation process challenging because objective trade-offs do not easily align when competing goals occur between objectives. Real-world validation usually reveals performance differences between simulated results and real-time performance because of hardware limitations as well as environmental uncertainties. The integration of Multi-Objective Particle Swarm Optimisation (MOPSO) into the present network infrastructure faces problems regarding system matching and system communications standards. The execution of MOPSO depends significantly on the correct selection of parameters, including population size, inertia weight, and acceleration coefficients. Fitting the right hardware configuration requires thorough testing because the search process is often laborious.

The deployment of MOPSO in real-time 5G network management systems encounters challenges since such systems need to execute decisions swiftly. To fulfill M2M communication latency requirements, the optimization process may require parallel or distributed computational methods at runtime. MOPSO procedures executed too frequently decrease the battery power of mobile M2M nodes; hence, proper implementation of interference reduction methods alongside computational efficiency may require adding adaptive algorithm start triggers as a solution.

6. Recommendations

A study should be conducted on adaptive Multi-Objective Particle Swarm Optimisation (MOPSO) through Dynamic Inertia Weight MOPSO and Adaptive Learning Particle Swarm Optimization, which boosts convergence speed and accuracy within dynamic 5G environments, studying the adaptive capabilities of these mechanisms when they need to maintain discovery and utilization of resources upon fast network transformations. MOPSO should be integrated with similar metaheuristic algorithms, such as GA and SA, to bypass local optima and accelerate convergence. Building a combined optimisation system that employs the advantages of both methods to boost Signal-to-Interference-plus-Noise Ratio (SINR) and achieve maximum throughput is imperative. Additionally, researchers need to develop low-energy versions of MOPSO that are suitable for weak computational devices used in M2M systems. Also, the implementation of Green MOPSO algorithms should aim to optimise energy consumption as a main optimisation goal. The current mathematical analysis requires the addition of Quality of Service (QoS) performance metrics for Ultra-Reliable Low-Latency Communication (URLLC) and massive Machine Type Communication (mMTC) system requirements. Techniques need to be developed to establish automatic adjustments of interference management approaches according to QoS requirements. A testbed with real-world conditions or a digital twin environment should be integrated into the proposed architectural implementation for performance assessment when facing mobile and dynamic interference scenarios. The proposed solutions should be tested against existing interference mitigation approaches that incorporate beamforming technologies, as well as power control and interference alignment implementations.

Furthermore, analysing the robustness, convergence speed, and computational efficiency of various techniques for optimising interference management. Utilize Reinforcement Learning (RL) or Deep Learning to dynamically adjust the parameters of Multi-Objective Particle Swarm Optimisation (MOPSO), such as inertia weight and acceleration coefficients, based on the network state and traffic conditions. Create a self-adaptive MOPSO framework that employs machine learning to predict optimal parameter settings. To evaluate the impact of interference mitigation on the performance of real-time grid monitoring and control systems, it is essential to explore interference management strategies that are resilient to adversarial attacks or malicious interference in 5G Machine-to-Machine (M2M) networks. Proposed secure optimisation frameworks that incorporate intrusion detection and interference prevention mechanisms are essential strategies that should be utilised. Additionally, the development of mobility-aware interference management models that dynamically update MOPSO optimization based on real-time device movement and handover scenarios, and also assess the influence of user mobility and handover frequency on interference patterns and the outcomes of the optimization process, should be explored.

7. Conclusion

In conclusion, the evolution of the 5G cellular standard brings new technologies that enhance its utilization. Emerging technologies such as Machine-to-Machine (M2M), Device-to-Device (D2D), and Vehicle-to-Vehicle (V2V) communication present challenges related to energy efficiency, spectral efficiency, and interference issues. The integration of these diverse devices has made Cellular User Equipments (CUEs) particularly susceptible to significant interference, which degrades the communication performance across the entire network. In this paper, we propose an interference-aware architecture tailored for the Nigerian power grid. Additionally, we mathematically modelled the interference scheme using the Multi-Objective Particle Swarm Optimization (MOPSO) method to optimize interference management. We expect that the results from our simulations will demonstrate a reduction in interference effects on the power grid, thereby enhancing the system's spectral efficiency.

Authors Contributions

Suleiman Ahmed Danasabe: Conceptualisation, Methodology, Drafting and writing the Original copy.

Mohammed Abubakar Saddiq: Validation, Supervision, and Proofreading.

Salihu Bala Alhaji: Validation, Supervision, and Proofreading.

David Micheal: Validation, Supervision and Proofreading.

Ibrahim Abdullahi: Assistance with simulation and optimization.

Micheal Ephraim: Proofreading and Editing of the final draft.

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Conflicts of Interest

All co-authors have seen and agree with the contents of the manuscript, and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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